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Anonymity, Membership-Length and Postage Frequency as Predictors of Extremist Language and Behaviour among Twitter Users

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Abstract
The rise in participation of social media networks is accompanied with a corresponding rise in online extremism. The present research was carried out to ascertain whether anonymity, membership length and postage frequency are predictors of online extremism. A total of 205 Twitter accounts and 102,290 tweets were examined. To address the research question, both a corpus linguistic analysis (CLA) and content analysis (CA) were conducted. The former looked at extreme words associated with Islam and the latter looked at four types of extremist behaviour (extreme pro-social, extreme anti-social, extreme anti-social prejudicial biases and extreme radical behaviours). Keyness tests demonstrated that extreme words were most significantly associated with Twitter accounts with high anonymity, low membership length and low postage frequency. A series of multiple regressions found that anonymity significantly predicted four types of extremist behaviour. Membership length only predicted extreme anti-social behaviour and postage frequency did not display any significant predictive power for any of the four types of extremist behaviour. These results suggest that anonymity, membership length and postage frequency differ in terms of predicting extremist language and behaviour.

Keywords: Extremism; Anonymity; Membership length; Postage frequency; Corpus linguistics.

Introduction

The emergence of the internet has provided individuals with a platform in which they can readily express themselves (Bryce, 2015). In January 2017 there were 3.77 billion internet users with 2.78 billion being active social media users, a 21 percent increase since 2016 (Chaffey, 2016). This rise has seen the proliferation of online extremism, with the internet acting as an echo chamber, which reinforces, distributes and popularises extremist content (Awan, 2017).

Violent extremism has contributed to the alienation of communities and creates inter-community tensions (Bartlett, 2010). Twitter allows users to connect for the purpose of

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sharing information (Gruzd, Wellman, & Takhteyev, 2011). Because of this, and how Twitter allows users to freely follow one another, tighter cluster effects around extremist content and stronger 'echo chamber' scenarios occur on Twitter (Gruzd, & Roy, 2014). The lack of moderation on Twitter combined with the rapid circulation of tweets presents extremists with the ability to effectively disseminate messages online, the ability to produce an accumulative effect through retweets, along with hashtags, pictures and URLs all adds to the magnitude and influence of their content (Blanquart, & Cook, 2013). Research has also demonstrated how there are linguistic and psychological properties amongst propaganda of ISIS extremism on Twitter (Nouh, Nurse, & Goldsmith, 2019). New social media genres like Twitter still require further analysis and research to fully address how extremism manifests online (Yardi & Boyd, 2010). To reduce extremism online, it is imperative to recognise and conduct analyses of how different types of extremism can occur online, addressing specific characteristics and behavioural themes for this will aid the development of tailored software.

A common form of extremism propagated in society is Islamophobia. Officials have recorded a fivefold increase in Islamophobia (Dodd & Marsh, 2017), with 74 percent of incidents occurring online (Awan, 2014). It has become increasingly commonplace on Twitter for extremists to demonise and dehumanise Muslim communities (Awan, 2014). Key extreme words that are associated with Islam, online, include: ISIS, terrorist and *jihad* (Awan, 2016; Baker, 2010; Mondal, Silva & Benevenuto, 2017).

Group polarisation is related to the occurrence of extremism (Sunstein, 2002). Within online groups, individual's preferences are polarised towards extreme positions, resulting in the engagement of harmful behaviours (Wojcieszak, 2010). Online polarisation has been found to occur in 'echo chamber' environments, where individuals are only exposed to other communities and information that coincides with their views. This leads them to be isolated from opposing viewpoints, thereby making their views more extreme (Gruzd, & Roy, 2014). As a result, the salience of extreme views increases in echo chamber environment like these (Gruzd, & Roy, 2014). These instances of people collecting together based on similar views and backgrounds have been referred to as homophily (McPherson, Smith-Lovin, & Cook, 2001). However, to fully understand the processes of polarisation research must gather data from different times scales (Stroud, 2010).

Significant links have been made between fragmentation and online extremism (Bright, 2018). Fragmentation is the notion that online communication is divided amongst dominant ideological lines, where individuals only access communication pools, in which they are accustomed to (Bright, 2018). The process of homophily has been said to cause the phenomenon of fragmentation to occur naturally on online platforms (Bright, 2018). This is closely related to selective exposure, where individuals pursue material that is cognitively similar to their own beliefs (Himelboim, Smith, & Shneiderman, 2013). Individuals who possess attitudes that hold extreme ideological attributes are more likely to perform selective exposure compared to those who hold not so extreme beliefs (Stroud, 2010). This behaviour has links to the hostile media theory, which states how individuals who hold extreme and already established beliefs will filter out alternative perceptions (Kim, 2011). This process acts as a self-reinforcing mechanism to further strengthen one's beliefs (Huckfeldt, Mendez, & Osborn, 2004). If one's echo chamber is one of extreme ideologies, then a user's online world will be saturated by deviant messages and the more they view this content the more saturated it will become (Akers, 1998; Aruguete & Calvo, 2018).

a. Overview, Rationale and Hypotheses

Research into cybersecurity focuses on the technological vulnerabilities such as malware rather than the influence that characteristics have on extremist communication online (Bryce, 2015). To mitigate online extremism, greater recognition of the factors involved in online extremism is needed to develop security solutions which focus on human factors rather than malware (Bryce, 2015). Currently the most common method to reduce online extreme content is manual reporting methods (Ferrara, Wang, Varol, Flammini, & Galstyan, 2016). These methods are not sufficient to reduce online extremism if the factors involved in online extremist language and behaviour are not fully understood. This research aims to encourage the development of systematic coding mechanisms that online networks can utilise to evaluate and assess levels of online extremism.

Research has failed to fully explore how levels of anonymity, membership length and postage frequency predict extremist behaviour online, such as; extreme pro-social, extreme anti-social, extreme anti-social prejudicial biases and extreme radical behaviours.

b. Factors Associated with Extremism

Anonymity minimises the perceived differences among individuals online, causing one to identify as a group– increasing polarisation towards extreme positions (Lee, 2006). Anonymity provides individuals with a sense of security and that levels of anonymity can influence how an individual will behave online (Christopherson, 2007). The deindividuation theory postulates that anonymity causes group members to fail to perceive themselves and others as individuals (Zimbardo, 1969). Deindividuation weakens inhibitions against non-normative behaviour (Festinger, Pepitone, & Newcomb, 1952). The social identity theory states that individuals have multiple social identities in certain contexts (Tajfel & Turner, 1986), anonymity can strengthen one's social identity and cause identification with group beliefs and expression of extreme views (Lea, Spears, & DeGroot, 2001).

The absence of a real name policy has popularised Twitter as a network for users to remain effectively anonymous and distribute and access material without being identified (Peddinti, Ross, & Cappos, 2017a). Extreme narratives online are potentially a product of a user's anonymity (Zhou, Qin, Lai, & Chen, 2007). The perceived anonymity in online environments produces different extremist behaviours compared to face-to-face interactions (Bryce, 2015). Further research needs to identify how different levels of anonymity are associated with extremist language and behaviour online.

Research has superficially explored the role of membership length and extremism online (Stroud, 2010). Extended membership within an echo chamber, towards a particular consensus, may increase the extremism of an individual's attitudes (Moscovici & Zavalloni, 1969). This might suggest that a longer online membership may increase one's opportunities to engage in extremism and be a part of an echo chamber, which could reinforce and strengthen these extremist views. Research has attempted to look at the tenure of membership but failed to fully establish the significant effects that it may have on extremism (Byrne *et al.* 2013). Due to the inconsistencies of the findings into membership length it is important to explore exactly how membership length is associated with levels of extremism online.

Online behaviour is also potentially affected by the degree of engagement, where a higher involvement results in a shift towards negativity and extremism (Del Vicario *et al.* 2016; Wojcieszak, 2010). Extremists such as ISIS, display very high postage frequency utilising methods such as videos to further project their extreme radical views (Awan, 2017). ISIS also disseminate online content in multiple languages to reach and recruit larger populations (Awan, 2017). Wojcieszak (2010) states research is needed to disentangle the findings and address the effects that online engagement has on the manifestation of extremist content.

c. Extremist Behaviours

With the emergence of Twitter radical behaviour has surged (Dean, 2016). Once being a positive and political attribute, the term radical now carries vast negativity (Dean, 2016). It is conflated with violence and terrorism even though one who is radical is not necessarily violent or a terrorist (Dean, 2016). It is possible for someone who displays radical behaviour to show signs of being a terrorist or express violent thoughts or behaviours, but this is not exclusive or always the case. A holistic definition of radical behaviour outlines how radical behaviour is where individuals have been introduced to an overtly ideological belief system, causing them to move away from moderate, mainstream beliefs (RCMP, 2009).

Reports of anti-social behaviour is becoming increasingly frequent online (Travis, 2014). The Crime and Disorder Act (1998) defines anti-social behaviour as the act of behaving in a manner that has caused or is likely to cause harassment or distress to others who are not part of the same household (Berman, 2009). Research has found that anonymity has increased anti-social behaviour online (Nogami & Takai, 2008).

Positive, pro-social interactions also occur online (DeAndrea, Tong, & Walther, 2011). Pro-social behaviour is an action that has the sole intention to benefit or help other people (Padilla-Walker & Carlo, 2015). Online pro-social behaviour is evident in the form of protection from aggressors (Amichai-Hamburger, Kingsbury, & Schneider, 2013; Lapidot-Lefler & Barak, 2015). Heerwegh (2005) states personalisation where users are identifiable, can help to facilitate pro-social behaviour.

1. METHOD

1.1. Design

This research employed a cross sectional design, comprised of two approaches. A CLA and a CA were performed to assess Twitter user's extremism in relation to anonymity, membership length and postage frequency. Anonymity was operationalised as the number of identifiable items associated with a Twitter user's account. A scoring system was generated to assign each Twitter user a score of identifiable items, for instance a full name was worth two points (partial one point), a potentially identifiable profile picture was worth one point, a specific location was worth two points (general location one point), and any additional links to social media profiles or personal information (like a date of birth) was worth an additional point. This classification of anonymity was believed to be more exhaustive compared to previous attempts by other research, which only focused on user's names and whether they have a URL (Peddinti, Ross, & Cappos, 2017b). Membership length was operationalised as the number of months active as a Twitter user. Postage frequency was classified as the average number of tweets per active month. This research measured two sets of dependent variables; one set derived from CLA (extreme language) and one set derived from CA (extreme pro-social, extreme anti-social, extreme anti-social prejudicial biases and extreme radical behaviour).

1.2. Corpus Based Approach

A CLA was utilised as it handles large data sets and produces high statistical reliability, whilst keeping corpora intact (Kennedy, 2014). This research used visual binning to create categorical variables from the three scale variables: anonymity, membership length and postage frequency. Each of the three scale variables were split into three categories, creating a total of nine categorical variables. Anonymity was split into low anonymity (characterised by five or six identifiable items), moderate anonymity (characterised by three or four identifiable items) and high anonymity (characterised by two or one identifiable items). Low anonymity represents high identifiability amongst Twitter users, whereas high anonymity represents low identifiability. Membership length was spilt into low membership length (characterised by a range of two to 23 months active), moderate membership length (characterised by a range of 23 to 64 months active) and high membership length (characterised by a range of 65 months to 114 months active). Postage frequency was spilt into low postage frequency (characterised by an average number of tweets per month between ten and 209), moderate postage frequency (characterised by an average number of tweets per month between 215 and 629) and high postage frequency (characterised by an average number of tweets per month between 648 and 13,346). A CLA was performed to assess how these nine categories of anonymity, membership length and postage frequency were associated with extreme words associated with Islam.

This research hypothesised that Twitter accounts with high anonymity (characterised by a low number of identifiable items), high membership length and high postage frequency will be significantly more associated with extreme words.

1.3. Content Analysis Approach

For the CA, the visual binning of the nine categorical variables were not utilised, instead anonymity, membership length and postage frequency were kept as scale data. For the purpose of the CA anonymity was measured and referred to as the number of identifiable items a Twitter user had. In addition to this, membership length was measured by the number of months active and postage frequency was measured by the average number of tweets per month. A CA was performed to assess how four different types of extremist behaviour can be predicted by levels of anonymity, membership length and postage frequency. The four types of extremist behaviour measured included; extreme pro-social, extreme anti-social, extreme anti-social prejudicial biases and extreme radical behaviour. For extreme pro-social behaviour this research looked at whether Twitter users supported and defended other users. For extreme anti-social behaviour, this research focused on whether users were harassing, offending or causing distress to other users. This research looked at specific anti-social prejudicial biases including homophobia, racism, fascism and sexism. This research operationalised radical behaviour as the adoption of an overtly ideological belief system, looking at how individuals have moved away from moderate, mainstream beliefs.

This research hypothesised that a higher number of identifiable items, lower levels of membership length and lower levels of postage frequency will significantly predict higher levels of extreme pro-social behaviour. This research also hypothesised that a lower number of identifiable items, higher levels of membership length and higher levels of postage frequency will predict higher levels of extreme anti-social behaviour, extreme anti-social prejudicial biases and extreme radical behaviour.

1.3. Participants

Utilising the recommendation that the minimum number of participants per predictor variable lies between 10 and 20 (Harrell, 2001; Schmidt, 1971), a total of 205 Twitter accounts and 102,290 tweets were examined. A snowball sample was utilised by selecting a base group of Twitter users. This was conducted by searching associated extreme words on Twitter, these search terms were based on wider literature highlighting extreme words associated with Islam (Awan, 2016; Baker, 2010; Mondal *et al.* 2017). Twitter accounts who were associated with these searches were used. Once several Twitter users had been selected, their accounts and interactions were used to recruit further participants.

1.4. Materials

AntConc computer software (Version 3.5.7) (Anthony, 2018), which encompasses a concordancer, keyword frequency generator, tools for cluster and lexical analysis (Anthony, 2004), was utilised to perform a CLA. FireAnt (Version 1.1.4) (Anthony and Hardaker, 2017), was used to collate tweets from Twitter accounts. A word list was required for the CLA. Using research looking at extremism (Mondal *et al.* 2017), Islamophobia (Awan, 2016) and representations of Islam and Muslims (Baker, 2010) a word list containing ten extreme words, such as terrorist and hate*,* was generated (see tables for full list).

1.5. Procedure

Participants were recruited using a snowball sample and were rated in terms of anonymity, membership length and postage frequency. FireAnt (Version 1.1.4) was used to collect and collate tweets from Twitter accounts, these were collected for both the CLA and the CA. Using AntConc (version 3.5.6), a CLA recorded keyness scores for the ten extreme words in relation to the nine categorical variables of anonymity, membership length and postage frequency. A CA measured the number of occurrences of participants' extreme pro-social, extreme anti-social, extreme anti-social prejudicial biases and extreme radical behaviours in relation to their anonymity, membership length and postage frequency. A corpus linguistic data collection sheet and a CA data collection sheet were used to record data. Data was collected in accordance to the British psychology society (2017) ethical guidance for internet mediated research.

1.6. Data Analysis Strategy

Two data analysis strategies were used to analyse the data collected. A total of nine keyness analyses was used to analyse the data from the CLA. A Keyness analysis was chosen as it performs a log-likelihood test which compares the frequency of a corpus of words against the frequency of a reference corpus (Anthony, 2004). The keyness analysis provides a p value which represents whether a word is significantly associated with a corpus of text, the keyness score represents how strong this significance is (Anthony, 2004). This indicates if a word is present significantly more in one corpus than another.

Four multiple regression analyses were conducted to analyse the data from the CA. These multiple regressions measured the association between the predictor variables: anonymity, membership length and postage frequency, and the criterion variables: extreme pro-social, extreme anti-social, extreme anti-social prejudicial biases and extreme radical behaviour.

2. RESULTS

1.1. Corpus Based Approach

Using AntConc (version 3.5.6) (Anthony, 2018), a total of nine analyses were performed on the nine categorical variables of anonymity, membership length and postage frequency. For the following results, negative keyness values represent words which are unusually infrequent compared to words in a reference corpus (Anthony, 2004).

1.2. Keyness tests

Table 1. Keyness analysis for low Anonymity and the word list

	Low Anonymity comparisons					
	Low anonymity vs Moderate anonymity			Low anonymity vs High anonymity		
Key terms	Frequency value	Keyness value	Significance value	Frequency value	Keyness value	Significance value
Isis	69	-148.25	<.001	-	-	-
Terrorist	23	-40.02	<.001	23	-61.45	<.001
Hate	-	-	-	91	-130.01	<.001
Die	-	-	-	34	-76.91	<.001
Kill	-	-	-	-	-	-
Suicide	-	-	-	-	-	-
Jihad	-	-	-	14	-44.44	<.001
Paki	-	-	-	-	-	-
Muzrat	-	-	-	-	-	-
Rapist	-	-	-	-	-	-

Table 2. Keyness analysis for Moderate Anonymity and the word list

	Moderate Anonymity comparisons					
	Moderate anonymity vs Low anonymity			Moderate anonymity vs High anonymity		
Key terms	Frequency value	Keyness value	Significance value	Frequency value	Keyness value	Significance value
Isis	658	+148.25	<.001	658	+386.58	<.001
Terrorist	198	+40.02	<.001	–	–	–
Hate	–	–	–	361	-130.56	<.001
Die	–	–	–	76	-199.51	<.001
Kill	–	–	–	–	–	–
Suicide	–	–	–	–	–	–
Jihad	–	–	–	53	-66.94	<.001
Paki	–	–	–	–	–	–
Muzrat	–	–	–	7	-306.33	<.001
Rapist	–	–	–	–	–	–

Table 3. Keyness analysis for High Anonymity and the word list

	High Anonymity comparisons					
	High anonymity vs Low anonymity			High anonymity vs moderate anonymity		
Key terms	Frequency value	Keyness value	Significance value	Frequency value	Keyness value	Significance value
Isis	–	–	–	477	-386.58	<.001
Terrorist	541	+61.45	<.001	–	–	–
Hate	1591	+130.01	<.001	1591	+130.56	<.001
Die	735	+76.91	<.001	735	+199.51	<.001
Kill	–	–	–	–	–	–
Suicide	–	–	–	–	–	–
Jihad	361	+44.44	<.001	361	+66.94	<.001
Paki	–	–	–	–	–	–
Muzrat	514	+155.1	<.001	514	+306.33	<.001
Rapist	–	–	–	–	–	–

Results shown in Tables one to three illustrate that the high anonymity corpus contains a higher number of extreme words which occur significantly more frequently when compared to both the low anonymity corpus and the moderate anonymity corpus. Additionally, results depict that the low anonymity corpus contains fewer extreme words which occur significantly less frequently when compared to both the high anonymity corpus and the moderate anonymity corpus.

Table 4. Keyness analysis for low membership length and the word list

	Low Membership length comparisons					
	Low membership length vs Moderate membership length			Low membership length vs High membership length		
Key terms	Frequency value	Keyness value	Significance value	Frequency value	Keyness value	Significance value
Isis	264	-299.07	<.001	-	-	-
Terrorist	787	+188.72	<.001	787	+347.57	<.001
Hate	1653	+557.36	<.002	1653	+147.84	<.002
Die	156	-309.23	<.001	-	-	-
Kill	757	+244.28	<.001	757	+303.61	<.001
Suicide	47	-502.27	<.001	-	-	
Jihad	653	+396.99	<.001	653	+266.23	<.001
Paki	-	-	-	-	-	-
Muzrat	-	-	-	16	-640.83	<.001
Rapist	-	-	-	-	-	-

Table 5. Keyness analysis for moderate membership length and the word list

	Moderate Membership length comparisons					
	Moderate membership length vs Low membership length			Moderate membership length vs High membership length		
Key terms	Frequency value	Keyness value	Significance value	Frequency value	Keyness value	Significance value
Isis	857	+299.07	<.001	857	+341.4	<.001
Terrorist	358	-188.72	<.001	-	-	-
Hate	610	-557.36	<.001	610	-142.28	<.001
Die	661	+309.23	<.001	661	+350.53	<.001
Kill	388	-244.28	<.001	-	-	-
Suicide	576	+502.27	<.001	576	+440.14	<.001
Jihad	136	-396.99	<.001	-	-	-
Paki	-	-	-	-	-	-
Muzrat	-	-	-	9	-715.14	<.001
Rapist	-	-	-	-	-	-

Table 6. Keyness analysis for high membership length and the word list

	High Membership length comparisons					
	High membership length vs Low membership length			High membership length vs moderate membership length		
Key terms	Frequency value	Keyness value	Significance value	Frequency value	Keyness value	Significance value
Isis	–	–	–	268	-341.4	<.001
Terrorist	244	-347.57	<.001	–	–	–
Hate	1128	-147.84	<.001	1128	+142.28	<.001
Die	–	–	–	156	-350.53	<.001
Kill	255	-303.61	<.001	–	–	–
Suicide	–	–	–	–	–	–
Jihad	–	–	–	–	–	–
Paki	–	–	–	–	–	–
Muzrat	586	+640.83	<.001	586	+715.14	<.001
Rapist	–	–	–	–	–	–

Table 7. Keyness analysis for low postage frequency and the word list

	Low postage frequency comparisons					
	Low postage frequency vs moderate postage frequency			Low postage frequency vs high postage frequency		
Key terms	Frequency value	Keyness value	Significance value	Frequency value	Keyness value	Significance value
Isis	377	-90.95	<.001	377	+42.67	<.001
Terrorist	794	+345.83	<.001	794	+282.19	<.001
Hate	–	–	–	–	–	–
Die	647	+411.52	<.001	647	+362.92	<.001
Kill	286	-196.01	<.001	–	–	–
Suicide	–	–	–	70	-353.07	<.001
Jihad	692	+327.01	<.001	692	+598.12	<.001
Paki	–	–	–	–	–	–
Muzrat	594	+766.07	<.001	594	+891.47	<.001
Rapist	–	–	–	–	–	–

Table 8. Keyness analysis for moderate postage frequency and the word list

	Moderate postage frequency comparisons					
	Moderate postage frequency vs low postage frequency			Moderate frequency vs high postage frequency		
Key terms	Frequency value	Keyness value	Significance value	Frequency value	Keyness value	Significance value
Isis	739	+90.95	<.001	739	+274.57	<.001
Terrorist	250	-345.83	<.0001	-	-	-
Hate	-	-	-	-	-	-
Die	134	-411.52	<.001	-	-	-
Kill	777	+196.01	<.001	777	+376.16	<.001
Suicide	-	-	-	-	-	-
Jihad	202	-327.01	<.001	202	+41.9	<.001
Paki	-	-	-	-	-	-
Muzrat	13	-766.07	<.001	-	-	-
Rapist	-	-	-	-	-	-

Table 9. Keyness analysis for high postage frequency and the word list

	High postage frequency comparisons					
	High postage frequency vs low postage frequency			High postage frequency vs moderate postage frequency		
Key terms	Frequency value	Keyness value	Significance value	Frequency value	Keyness value	Significance value
Isis	269	-42.67	<.001	269	-274.57	<.001
Terrorist	336	-282.19	<.001	-	-	-
Hate	-	-	-	-	-	-
Die	184	-362.92	<.001	-	-	-
Kill	-	-	-	225	-376.16	<.001
Suicide	562	+352.07	<.001	562	+399.91	<.001
Jihad	104	-598.12	<.001	104	-41.9	<.001
Paki	-	-	-	-	-	-
Muzrat	4	-891.47	<.001	-	-	-
Rapist	-	-	-	-	-	-

Findings shown in tables four to six show that the low membership length corpus contains more words which occur significantly more frequently when compared to both the moderate membership length corpus and the high membership length corpus. Additionally, results depict that the high membership length corpus contains less words which occur significantly less frequently when compared to both the low membership length corpus and the moderate membership length corpus.

Tables seven to nine demonstrate that the low postage frequency corpus contained more words which occur significantly more frequently when compared to both the moderate postage frequency corpus and the high postage frequency corpus. Additionally, results depict that the high postage frequency corpus contains less words which occur significantly less frequently when compared to both the low postage frequency corpus and the moderate postage frequency corpus.

Overall, the CLA indicates that extremist language was present significantly more often in the high anonymity, low membership length and low postage frequency corpora.

2.3. Content Analysis Approach

A total of four multiple regressions were conducted to analyse whether levels of anonymity, membership length and postage frequency predicted levels of extreme pro-social, extreme anti-social, extreme anti-social prejudicial biases and extreme radical behaviour. Assumptions of multicollinearity were met for all regressions.

2.4. Extreme pro-social behaviour

A multiple regression was run to predict the variability in extreme pro-social behaviours (M=3.41; SD= 11.61) using Identifiable items (anonymity) (M=1.89, SD=1.53), months (membership length) (M=46.98, SD=33.35) and average tweets per month (postage frequency) (M=787.17, SD=1396.44).

Together the predictor variables explained 26.9 percent (Adjusted R^2 = .269) of the variability of extreme pro-social behaviour. The overall association between the predictor variables and extreme pro-social behaviour was significant, $F(3, 201) = 26.03$, $p<.001$. The predictor variable identifiable items (b=3.80; $p<.001$) displayed a significant and positive association with extreme pro-social behaviour, when the number of identifiable items increased, extreme pro-social behaviour also increased. Two of the predictor variables months (b=.033; p=.127) and average tweets per month (b= -.001; p=.076) did not display a significant association with extreme prosocial behaviour.

2.5. Extreme anti-social behaviour

A multiple regression was run to predict the variability in extreme anti-social behaviour (M=35.12; SD=19.84) using months (membership length) (M=46.98; SD=33.35), average tweets per month (postage frequency) (M=787.17; SD=1396.44) and identifiable items (M=1.89; SD=1.1535).

Together the predictor variables explained 16.7 percent (Adjusted R^2 = .167) of the variability in extreme anti-social behaviour. The overall association between the predictor variables and extreme anti-social behaviour was significant, $F(3, 201)= 14.62$, $p<.001$. The predictor variable Months (b= -.078; $p=.047$) displayed a significant and negative association with extreme anti-social behaviour. The lower the number of months active, the higher the occurrence of extreme anti-social behaviours - as the number of months increased the amount of extreme anti-social behaviour decreased. The predictor variable Identifiable items (b= -4.986; $p<.001$) displayed a significant and negative association with extreme anti-social behaviour. The lower the number of identifiable items the higher the occurrence of extreme anti-social behaviour – as the number of identifiable items increased the amount of extreme anti-social behaviour decreased. The predictor variable average tweets per month (b= 2.22; p =.981) did not display a significant association with extreme anti-social behaviour.

2.6. Extreme anti-social prejudicial biases

A multiple regression was run to predict the variability in anti-social prejudicial biases (M=46.52, SD= 37.88) using months (membership length) (M=46.98; SD=33.35), average tweets per month (postage frequency) (M=787.17; SD=1396.44) and identifiable items (M=1.89; SD=1.153).

Together the predictor variables explained 13.8 percent (Adjusted R^2 .138) of the variability in anti-social prejudicial biases. The overall association between the predictor variables and anti-social prejudicial biases was significant, $F(3, 201) = 11.93$, $p < .001$. The predictor variable identifiable items (b= -8.367; $p<.001$) displayed a significant and negative association with anti-social prejudicial biases. The lower the number of identifiable items the higher the occurrence of extreme anti-social prejudicial biases– as the number of identifiable items increased the amount of extreme anti-social prejudicial biases decreased. The two predictor variables months (b= -.119; p=.120) and average tweets per month (b= -.003; p=.083) did not display a significant association with anti-social prejudicial biases.

2.7. Extreme Radical Behaviour

A multiple regression was run to predict the variability in extreme radical behaviour (M=9.43, SD=9.75) using months (membership length) (M=46.98; SD=33.35), average tweets per month (postage frequency) (M=787.17; SD=1396.44) and identifiable items (M=1.89; SD=1.153).

Together the predictor variables explained 10.6 percent (Adjusted R^2 .106) of the variability in extreme radial behaviour. The overall association between the predictor variables and extreme radical behaviour was significant $F(3, 201) = 9.09$, $p<.001$. The predictor variable identifiable items (b= -1.966; p <.001) displayed a significant and negative association with extreme radical behaviour. The lower the number of identifiable items the higher the occurrence of extreme radical behaviour – as the number of identifiable items increased the amount of extreme radical behaviour decreased. The two predictor variables months (b= -.024; p=.228) and average tweets per month (b= -.001; p=.187) did not display a significant association with extreme radical behaviour.

3. DISCUSSION

3.1. Corpus Based Approach

As hypothesised, the present research found that Twitter accounts who have high anonymity, where the number of identifiable items is low, are significantly more associated with extreme words - compared to other levels of anonymity. These results coincide with wider literature which elucidates how levels of anonymity can influence how an individual will behave online (Christopherson, 2007). In particular it provides evidence to support theoretical claims which suggest how a user's level of anonymity can influence them to propagate extreme narratives online (Zhou *et al.* 2007).

This research did not support the hypothesis outlining that Twitter accounts with a high membership length will be significantly more associated with extreme words, compared to other levels of membership length. This research found that a higher number of extreme words occurred significantly more frequently for Twitter accounts with a low membership length. This disputes wider research that has suggested high membership length is associated with non-normative behaviour online (Byrne *et al.* 2013; Moscovici & Zavalloni, 1969).

Literature around risks and investments may explain why a higher number of extreme words occurred significantly more frequently for Twitter accounts with a low membership length. Simon (1955) suggested how humans are bound by investments and costs which constrain an individual's behaviour. The reason why short-term members display high evidences of extreme words could be linked to their perceived risk, as a newer user the individual may have less emotional attachment to their account and have less concern about potentially losing followers, or even their account. They proceed to exert extreme narratives without a concern. Those that have been long-term members may have a stronger follower count and have a stronger emotional attachment to their Twitter account. Their investment in producing a robust Twitter account may result in them being less willing to risk it by exerting extreme narratives online. Research supports the current findings, finding that spending less time online and having a lower membership length correlates with the production of hate and extremism online (Costello & Hawdon, 2018).

The social identity theory (Tajfel & Turner, 1979; Tajfel & Turner 1986) may explain why a higher number of extreme words occurred significantly more frequently for Twitter accounts with a low membership length. Individuals enhance the status of a group which they belong to and go through a process of social identification, where they adopt the identity of a group and act to conform to the group in order to feel a sense of belonging (Tajfel & Turner, 1979; Tajfel & Turner 1986). These processes are necessary for new members to successfully integrate into a group (Tajfel & Turner, 1979; Tajfel & Turner 1986). Twitter users with a low membership length may be more associated with extreme narrative as they are attempting to enhance their status within the echo chamber, making sure to conform to its norms by propagating more extremism to feel a sense of identity and belonging. Long term members may have already established their role and identity within the community.

This research did not support the final hypothesis for the CLA, which stated that Twitter accounts with a high postage frequency, will be significantly more associated with extreme words. This research found that a higher number of extreme words occurred significantly more frequently for Twitter accounts with a low postage frequency. These findings dispute previous literature that states how a higher engagement online results in a shift towards exerting extremism (Del Vicario *et al.* 2016). However, this previous research arguably failed to demonstrate a clear relationship between online engagement and extremism (Wojcieszak, 2010).

An explanation for this relates back to the findings from the membership length condition. A Twitter user's Postage frequency is relative to their length of membership (Statista, n.d.), therefore it is likely that an account with a low membership length will also have a lower postage frequency. Since, the present research found that Twitter accounts with a low membership was significantly associated with more extreme words, it is logical that a higher number of extreme words also occurred significantly more frequently for Twitter accounts with a low postage frequency.

3.2. Content Analysis Approach

The results of the CA provide partial support for the proposed hypotheses. As hypothesised for the extreme pro-social predictor variable a higher number of identifiable items significantly predicted higher levels of extreme pro-social behaviour. These findings coincide with literature stating that personalisation online helps to facilitate pro-social behaviour (Heerwegh, 2005). It also supports findings that in order to increase normative behaviours like pro-social acts, the internet requires measures to reduce the anonymity of online users (Krysowski & Tremewan, 2015).

This research, like hypothesised, demonstrated that a lower number of identifiable items significantly predicted higher levels of extreme anti-social behaviour, extreme anti-social prejudicial biases and extreme radical behaviour. Wider literature concurs with these findings stating how anonymity increases an individual's polarisation towards extreme positions (Lee, 2006).

This research did not support the hypothesis that predicted that a longer length of membership would predict higher levels of extreme anti-social behaviour. This research did find a significant association between membership length and extreme anti-social behaviour but found that a lower number of months active was significantly associated with a higher occurrence of extreme anti-social behaviours. These findings challenge wider literature that states that online users with an extended membership are likely to demonstrate more extremist behaviour (Moscovici & Zavalloni, 1969). The findings of the present research disputes previous literature that failed to find any significant effects that a user's membership length may have on their level of extremism (Byrne *et al.* 2013). The findings from the CA for the membership length condition, mirror the findings and potentially the explanations from CLA of membership length. These explanations include theories relating to risk and investments (Simon, 1955) and also the social identity theory (Tajfel & Turner, 1979; Tajfel & Turner 1986).

The hypothesis outlining that lower levels of postage frequency would be significantly associated with higher levels of extreme pro-social behaviour was not supported. The current research also failed to support the hypotheses stating that higher levels of postage frequency would predict higher levels of extreme anti-social behaviour, extreme anti-social prejudicial biases and extreme radical behaviour. These findings challenge wider literature that has documented that a higher engagement online results in a shift towards extremism (Del Vicario *et al.* 2016; Wojcieszak, 2010).

In attempts to elucidate this relationship, the present research demonstrated that even when looking at four different types of extremist behaviour, postage frequency failed to display any significant association. It seems apparent that postage frequency does not hold strong predictive power for the potential extremist behaviours that occur online. It is important to recognise that the two approaches, the CLA and the CA, were looking at two distinct areas of extremism, language and behaviour. This can explain why CLA and the CA demonstrated different findings in relation to postage frequency.

Recommendations

The present research specifically looked at extremism on Twitter, using Twitter users as participants. There are evidential differences between Twitter and other social media sites (Gruzd, Wellman, & Takhteyev, 2011; Gruzd, & Roy, 2014). This Suggests that there are potential differences in the way extremism is disseminated across these different platforms. It is recommended that future research should replicate the present research on other social media networks, such as Facebook, to fully determine any differences in the way that predictive factors play a role in producing extremism online (Conway, 2016).

To further understand how factors, predict online extremism the present research should be extended by looking at additional predictor variables. It is suggested that the follower count of social media users is associated with instances of extremism (Benigni, Joseph, & Carley, 2017). It is important to demonstrate whether follower count can act as a predictor of online extremist language and behaviour.

Conclusion

The present research was carried out to ascertain how factors including anonymity, membership length and postage frequency act as predictors for online extremism. Although several hypotheses were not supported, the present research demonstrated how anonymity, membership length and postage frequency differ in terms of predicting various types of online extremism. This research in particular, highlighted how these three variables are associated with both extreme narratives and extreme behaviours. This research has outlined suggested the investigation of further predictor variables and replicating the present research using other sample populations. The present research has important implications in terms of developing legislative measures, producing software to reduce online extremism, identifying accounts associated with extreme language, and encouraging the reduction of the anti-muslim rhetoric by avoiding extreme words associated with Islam.

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